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Measuring Consumption in 12 Minutes: Lessons from a field study in Rural Kenya

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Measuring Consumption in 12 Minutes: Lessons from a field study in Rural Kenya

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Abstract

Detailed measurement of consumption expenditure is the gold standard for welfare analysis in a low-income mixed-livelihoods setting, but is demanding of respondent time and survey resources. We developed a short consumption module in the context of a field study in rural Western Kenya that required under 12 minutes survey time on average in the sample. We document development of the module and construction of the consumption aggregate, exploring alternative imputation methods. Simulation-based analysis allows us to assess the potential of our approach for application to impact evaluation and distributional analysis, for example poverty monitoring. There is a trade-off between sample density and potential time savings.

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1 Introduction

Comprehensive measurement of consumption expenditure – including value of consumption from purchases, own-production and gifts and transfers – is the standard approach to the evaluation of material wellbeing in a low-income context. As discussed by Ravallion (1994) and Deaton (1997), it is more straightforward to evaluate consumption expenditure than (net) income for a household practising mixed livelihoods strategies in a low-income context, while consumption reflects any intertemporal smoothing strategies practised by the household, and is thus less sensitive to seasonal fluctuations as well as a better proxy for experienced material wellbeing. Where available, per capita consumption expenditure from representative household surveys forms the basis for national and international monetary poverty monitoring (see World Bank, 2018, for recent international estimates).

However, the comprehensive measurement of a household's consumption expenditure requires lengthy questionnaire modules, and is thus very demanding on both the respondent's time and the surveying institution's resources. The resource implications mean that most low-income countries are limited in the frequency and geographical comprehensiveness with which they can monitor poverty, while many research studies, including policy evaluations, are not able to evaluate impacts on material wellbeing as measured by consumption expenditure. Deaton et al. (1998) discuss the tradeoffs between survey length and measurement accuracy on the one hand, and time and resource on the other, noting that LSMS surveys have generally included shorter consumption modules than national household budget surveys, but that these are still long. They reviewed the developing literature on questionnaire design for consumption expenditure measurement, noting that the evidence available was mixed, with no clear guidance available on optimal questionnaire design.

Nevertheless, it is clear when working with consumption data from a low-income context that at item level there is considerable information redundancy, so in principle it should be possible to develop more efficient approaches to measurement. In recent years a number of experimental studies have explored the possibilities for less-resource-intensive measurement of consumption expenditure. Beegle et al. (2012) compare alternative approaches to shortening consumption modules in Tanzania, while Pape and Mistiaen (2018) combined randomisation of sub-modules and imputation to reduce survey length to 60 minutes in Somalia.

In 2016 we developed a short consumption module for the baseline survey of an experimental study in rural Western Kenya (Orkin et al., 2019). We sought to measure consumption expenditure as accurately as possible (including own-valuation of items consumed from own-production, gifts and transfers) within tight survey-time constraints, in order to be able to measure welfare impacts meaningfully and to make possible the distributional analysis required for a companion study (Dercon et al., 2016). Guided by the findings of Beegle et al. (2012), we restricted our food and regular non-food item lists to those items that we expected to contribute the greatest share to households' total consumption expenditure.

Developing the endline questionnaire in 2018, we faced two further challenges: even tighter survey-time constraints, and the need to compute the scale factors necessary to combine the different elements into a consumption aggregate comparable to the aggregate developed for national poverty analyses (Kenya National Bureau of Statistics, 2018). Using the baseline data allowed us shorten the item lists further, while we implemented a radical version of the sub-module randomisation approach introduced by Pape and Mistiaen (2018) to establish the necessary scalefactors.

In this paper we document our approach and begin to evaluate the extent to which it can accurately capture household consumption expenditure. In section 2 we document the design of the consumption modules in the baseline and endline household questionnaires. In section 3 we outline alternative imputation methods. We use simulation methods to explore possibilities for optimal consumption module design in section 4. Section 5 concludes.

2 Module Design

2.1 Food: Baseline

The experimental study, in the context of which we developed our consumption measurement approach, was carried out in rural villages in two counties in Western Kenya, Homa Bay and Siaya. Within Homa Bay, the study area corresponded closely to rural parts of the pre-2013 administrative area Rachuonyo District, while within Siaya, the study area corresponded closely to rural parts of the pre-2013 Bondo District. Baseline data collection commenced in April 2016 in Homa Bay and in October 2016 in Siaya.

To develop the food consumption module we followed the 'subset list' approach of Beegle et al. (2012), attempting to identify a subset of food consumption items that captured as much as possible of food consumption expenditure. The best available reference data was the 2005/06 Kenya Integrated Household Budget Survey (KIHBS05/06),[1] whose consumption module comprised a fairly comprehensive list of 107 items. As our survey imple-

[1]Kenya Integrated Household Budget Survey 2005-2006, Version 1.0 of the KNBS dataset.

mentation started in Homa Bay, we based our preliminary analysis on the 170-household KIHBS05/06 subsample from Rachuonyo District.

Table 1: Analysis of KIHBS05/06 Food Items (Rachuonyo District)

KIHBS code	**KIHBS description**	**Rank**	**Average proportion**	**Description**	**Total proportion**
105	Maize Flour – Loose	1	0.0778	Maize Flour	0.0814
103	Maize Grain – Loose	2	0.0755	Maize Grain (include grain ground at mill)	0.0755
1101	Sugar	3	0.0727	Sugar	0.0727
701	Fresh fish	4	0.0695	Fresh Fish	0.0695
703	Dried/smoked fish	5	0.0493	Dried/Smoked Fish	0.0493
801	Milk - fresh unpacketed	6	0.0486	Fresh Milk	0.0636
501	Beef - with bones	7	0.0424	Red Meat (beef/mutton/goat)	0.0454
301	Beans	8	0.0363	Beans	0.0363
904	Cooking Fat	9	0.0363	Cooking Fat	0.0363
406	Kale-Sukuma wiki	10	0.0304	Kale - Sukuma Wiki	0.0304
404	Tomatoes	11	0.0299	Tomatoes	0.0299
101	Rice Grade 2	12	0.0281	Rice	0.0301
419	Other vegetables	13	0.0269	*Mystery Vegetable*	0.0269
506	Chicken	14	0.0254	Chicken and other poultry	0.0254
116	Bread	15	0.0248	Bread (only if purchased)	0.0248
305	Groundnut	16	0.0245	Groundnuts	0.0245
202	Sweet potato	17	0.0228	Sweet Potato	0.0228
208	Cooking banana	18	0.0178	Cooking Banana	0.0178
802	Milk - fresh packeted	19	0.0150	—	
112	Sorghum flour	20	0.0142	Sorghum (grain or flour)	0.0225
1001	Banana - ripe	21	0.0136	Ripe Banana	0.0136
1402	Sodas	22	0.0118	Sodas	0.0118
204	Cassava	29		Cassava (flour or root)	0.0118
	Total		**0.7935**	**Total**	**0.8266**

Source: Kenya Integrated Household Budget Survey 2005-2006, Version 1.0 of the KNBS dataset. $N = 170$, Rachuonyo District sub-sample. Authors' calculations.

Table 1 reports the results of our preliminary analysis. Computing the average proportion of each item in sub-sample households' total food consumption expenditure, the top 22 ranked items (just 20.6% of the list) achieved coverage 79.35% (column 4) and this short list provided the starting point for development of our food item list. It is interesting to observe that the items identified cover both local staple foodstuffs (notably maize) and relatively luxurious goods (rice, meat). Although the luxurious goods are eaten by a smaller proportion of households, when consumed they account for a significant proportion of the expenditure and thus contribute significantly to the average proportion. Meanwhile, 'necessary' goods including salt and onions, consumed in small quantities by almost all households, are excluded. Encouragingly, this suggests that the approach implemented has the potential to capture a good proportion of the variation in consumption expenditure.

Clearly the KIHBS05/06 item 'Other vegetables' only made sense in the context of a comprehensive list of specified vegetables; through survey piloting we determined that 'African nightshade', locally Osuga or Managu, was a very commonly eaten local vegetable that likely explained most of the high proportion of consumption of 'other vegetables' in the subsample data.

Aware of the under-reporting dangers of excessive amalgamation (Deaton et al., 1998; Beegle et al., 2012), we nevertheless identified through survey piloting a few sets of items that could be combined without ambiguity, for example rice of different grades, and fresh milk whether packeted or unpacketed. Combined descriptions are found in column 5, with combined proportions in column 6. As both types of milk had appeared in our shortlist, we filled the vacated space with (combined root and flour) cassava, bringing the total estimated coverage to 82.66%.

Of course, this preliminary analysis was based on a small sample, not necessarily representative of our study population, over a decade had elapsed since the KIHBS05/06 survey was conducted in which time tastes may have changed, and it is possible that consumption patterns in the study area exhibit strong seasonality effects. We therefore expected that actual coverage might be somewhat less, and actively sought feedback in piloting to identify any important food items that had been missed. This resulted in the addition of Omena,[2] Mandazi (integrated with bread), Groundnuts and Chapati to our food list. Conversely, Sodas and Ripe Banana were found to be very minor items in piloting, and were dropped from the list. The final list fielded in Homa Bay thus constituted 22 items.

Repeating the preliminary analysis with the Bondo District sub-sample of the KIHBS05/06 data identified a similar list of items, but Oranges (code 1002), Beer (code 1503) and Pawpaws (code 1003) were identified among the items that accounted for the highest pro-

[2]Omena are dried small fish from Lake Victoria and are a staple protein source locally. Interestingly, they were not included in the KIHBS05/06 item list, presumably because of their localised availability. Feedback from piloting clearly indicated that they were locally regarded as a very different foodstuff from dried or smoked fish. We therefore decided to include them as a separate item.

portion of consumption, so we added them to the item lists fielded in Siaya county which thus constituted 25 items.

2.2 Food: Endline

Endline survey data collection commenced in May 2018. At endline we faced tighter survey time constraints than at baseline and after piloting with the same item lists as at baseline, we were forced to make cuts. At the time of survey design the 2015-2016 Kenya Integrated Household Budget Survey data were not publicly available, so rather than returning to the 12-year-old KIHBS05/06 data we analysed the study baseline data in order to identify those items that accounted for the smallest proportion of food consumption expenditure. This analysis allowed us to drop several items from the core food list (Sorghum, Chapati, Cassava, Groundnuts and the Siaya extra items, Oranges, Beer and Pawpaws) reducing it to 18 items in total.

At endline, we tackled a critical issue that had not been addressed at baseline: having collected data on a subset of food items that we know are not comprehensive, how to determine the appropriate scale factor for food consumption that would allow us to aggregate it with other classes of item? This would also allow us to assess just how comprehensively our shortened food list had allowed us to capture total food expenditure. There existed no reference dataset sampled from the same population, so we had to be able to collect the necessary data within tight time contraints in our own sample.

Pape and Mistiaen (2018) addressed a similar problem by dividing non-core items in a comprehensive list into sub-modules of similar length to the core list, randomising the allocation of the non-core submodules to respondents, then carrying out statistical imputation to 'complete' their consumption aggregate. We attempted to emulate this approach to the extent that our time constraints allowed, dividing non-core items into 29 submodules of just three items that were randomly allocated to respondents in the field. With a sample size of over 10,000 households, this permitted a sample size of over 300 households for each non-core item.

2.3 Other Modules

Our module capturing regularly purchased non-durable non-food items was developed through a similar approach to the food module; at baseline we included 18 core items, cut to 11 at endline. At endline 31 non-core items were individually randomly allocated to respondents to permit estimation of consumption shares and thus scaling of the non-food non-durable aggregate.

We attempted to implement a similar approach for durable items, but the approach described above was not effective; as these items are so lumpy it was impossible to identify a subset of the KIHBS05/06 item list that accounted for a significant share of expenditure across households. Time constraints required us to shorten the list, so in this case we aggregated items into natural categories and relied on the untested assumption that the salience of such lumpy purchases would minimise the resultant risk of under reporting. Similarly, the few social expenditures needed for the consumption expenditure aggregate were included unmodified.

Education expenditures were captured by child in the household roster; the time required was not counted in our 12 minute estimate of consumption module duration.

3 Construction of the Consumption Aggregate

Consumption expenditure, defined in detail in Orkin et al. (2019)[3], is an aggregate of the following components:

1. **Food consumption** Aggregate of 18 core items (7 day recall) scaled by food scale factor and to 30 days.
2. **Non-food, non-durable consumption** Aggregate of nine core items (30 day recall) scaled by non-food scale factor.
3. **Durable goods** Value of expenditure on purchase and maintenance of durable items over 12 months, scaled to 30 days.
4. **Social expenditure** Aggregate of five items, all scaled to 30 days.
5. **Education expenditure** Aggregate of 18 core items (7 day recall) scaled by food scale factor and to 30 days.

We focus here on derivation and computation of the scale factors for the food and non-food, non-durable components.

3.1 Scale Factor Imputation

Let the total food consumption of household h be $F_h = \sum_{i=1}^{I} c_{ih}$, where c_{ih} is household h's consumption of item i, items being indexed $i = 1, 2, \ldots, I$. Let items $i = 1, 2, \ldots, K$

[3] In Appendix B of which are found the detailed item lists.

be included in the core list, and items $i = K+1, \ldots, I$ not. Then

$$F_h = \sum_{i=1}^{I} c_{ih} = \sum_{i=1}^{K} c_{ih} + \sum_{i=K+1}^{I} c_{ih} = C_h + N_h$$

where $C_h = \sum_{i=1}^{K} c_{ih}$ is the household's (observable) total consumption of core items, while $N_h = \sum_{i=K+1}^{I} c_{ih}$ is the household's (unobservable) consumption of non-core items.

Suppose that household h has homothetic preferences over food items, separable from other consumption items. (If relative prices do not vary then C_h is a meaningful aggregate and the assumption of homotheticity must be maintained for C_h but may be dropped for its components.) In that case, consumption of each of the different non-core items will scale in proportion to the household's core food consumption, so $c_{ih} = \alpha_{ih} C_h$ where each $\alpha_{ih} \in [0, 1)$ (typically much less than 1) and $\alpha_h = \sum_{i=K+1}^{I} \alpha_{ih} \in [0, 1)$. Then

$$F_h = C_h + \sum_{i=K+1}^{I} \alpha_{ih} C_h = (1 + \alpha_h) C_h.$$

If we could measure the α_{ih} for household h then we could compute C_h; however, that would require a full consumption module. If we are prepared to assume homogeneity of the non-core food preferences across households then $\alpha_{ih} = \alpha_i$ for each $i = K+1, \ldots, I$. In that case, the α_is and thus $\alpha = \sum_{i=K+1}^{I} \alpha_i$ may be estimated from the non-core food consumption data.

3.1.1 Estimation of the Scale Factors

We may apply the analysis above to estimate the scale factors needed for the food and non-food non-durable sub-aggregates. For each extra food item i, we first compute consumption expenditure value as the proportion of core food consumption for each household h in the subsample N_i to whom that item was randomly allocated, $\hat{\alpha}_{ih}$. We then estimate the population mean proportion by the subsample average; $\hat{\alpha}_i = \frac{1}{N_i} \sum_{h \in N_i} \hat{\alpha}_{ih}$. Then $\hat{\alpha} = \sum_{i=K+1}^{I} \hat{\alpha}_i$ and we may impute each household's total food consumption as $\hat{F}_h = (1 + \hat{\alpha}) C_h$.

[Data/results under embargo]

3.1.2 Descriptive Statistics for the Consumption Aggregate

As a first assessment of the approach implemented, we compare descriptive statistics with the comprehensive consumption aggregates constructed, as comparably as possible, from the KIHBS15/16 data.

[Data/results under embargo]

3.2 Alternative Imputation Methods

We showed above that under some very restrictive assumptions, the scale factor approach to imputation is perfectly valid and will allow (asymptotically) precise measurement of total food consumption. In practice, of course, these assumptions will not hold. Most importantly, preferences for many of the non-core items are clearly far from homothetic; some are luxury goods and are consumed only by the wealthier households, while others are necessities, scaling slower than proportionally with core food consumption. It is also possible that there is significant taste heterogeneity across different households.

Simulation approaches (see section 4 below) will allow us to explore the potential impact of these effects on accuracy of the total consumption measure. However, it is also possible that we can do better with the same data. As the scaling of the restricted aggregate is an imputation problem, we will explore alternative methods to will include regression-based single and multiple imputation approaches.

4 Optimal Module Design

[Work in progress]

5 Concluding Remarks

In this paper we contribute to the developing literature on efficient consumption expenditure measurement by documenting and assessing the radical approach that we implemented in the context of a field study in rural Western Kenya. We are able to draw some conclusions that have wider applicability, noting in particular our quantification of the trade-off between module length and sample density for a given measurement accuracy objective. Full assessment of the approach that we developed will require future experimental implementation.

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